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Abstract

Monetary lotteries are the overwhelmingly predominant tool for understanding decisions under risk. However, many real-world decisions concern multidimensional outcomes involving different goods. Recent studies have tested whether people treat multidimensional risky choices in the same manner as unidimensional monetary lotteries and found that choices over consumer goods are less risk-averse and more consistent with expected utility theory than choices over monetary lotteries. While these puzzling results cannot be explained by any standard model of decision making, we demonstrate that these findings are predicted by a salience-based model of category-dependent preferences that also explains the classic anomalies for choices under risk. Additionally, we experimentally verify a novel prediction of this Categorical Salience Theory. We further demonstrate that our model can explain empirical puzzles in financial markets, insurance markets, and principal agent settings, including behavior in a new portfolio choice experiment that is unexplained by expected utility theory or prospect theory.

Keywords: Salience; Categorization; Choice under Risk

JEL Codes: D90, D91

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1 Introduction

Many decisions involve uncertainty about outcomes, such as how a consumer's diet and exercise regimen will affect long-term health, whether to purchase a shirt or pair of sneakers from Amazon.com without knowing if they will fit comfortably, and whether to open Door number 2 or Door number 3 on a television game show in order to maximize the probability of winning a new car. Many decisions also involve multi-dimensional outcomes. For instance, the choice to order triple chocolate cheesecake for dessert may result in both utility from consumption and disutility from gaining weight. The decision to speed may save time, but may also result in personal injury. However, despite the ubiquity of decisions under uncertainty that involve non-financial outcomes or multidimensional outcomes, the vast research on decisions under risk has focused primarily on unidimensional monetary lotteries.

Going back at least as far as 1738 with Bernoulli's work on the St. Petersburg Paradox, monetary lotteries have been the workhorse framework for understanding decisions under risk. Recent studies have tested whether people treat multidimensional risky choices the same as unidimensional monetary lotteries and found systematic differences. In particular, revealed preferences over consumer goods are less risk-averse (DeJarnette, 2017) and more consistent with expected utility theory (Arroyos-Calvera et al., 2018) than revealed preferences over monetary lotteries. These puzzling results cannot be explained by any standard model of decision making.

We demonstrate that these findings are predicted by a salience-based model of behavior that also explains the classic anomalies for choices under risk. In particular, we generalize the salience theory of Bordalo et al. (2012) to multidimensional outcomes. The essence of our approach is to assume that, rather than grouping outcomes into 'salient states,' individuals group outcomes into 'categories.' The predictions of our model coincide with those of salience theory when all outcomes are from a single category. Our approach thus links to two fundamental concepts in psychology and behavioral economics – salience perception and categorization to individual choices under risk. We refer to the resulting model as categorical salience theory (CST). CST adds no additional parameters to salience theory given any categorization of outcomes, and it reduces to the Bordalo et al. (2012) salience model when there is a single category. The CST model also has fewer parameters than cumulative prospect theory (Tversky and Kahneman, 1992), while generating novel predictions that more strongly distinguish it from prospect theory and other models of choice under risk than are provided by salience theory for monetary lotteries.

After applying CST to basic choices between lotteries, we consider the implications of CST for a variety of economic contexts. O'Donoghue and Somerville (2018) argue that three of the primary applications for behavioral models of choice under risk should be financial markets, insurance markets, and principal-agent settings. We show how CST can explain empirical puzzles in each of these domains: the higher demand for categorized insurance, the effectiveness of non-monetary incentives in employment contracts, greater variety seeking in simultaneous than in sequential choice, and naive diversification across financial assets.

The paper is structured as follows. Section 2 introduces the generalization of salience theory to risky choices involving multidimensional outcomes. Section 3 applies this theory to explain choices between lotteries over multidimensional outcomes. In particular, we apply CST to explain differences in risk preferences over money compared to goods from prior experimental studies and report a new study examining risk preferences across categories of goods to provide a direct test of CST. We then apply CST to different economic contexts including portfolio choice (Section 4), insurance (Section 5), and employment contracts (Section 6). Section 4 also reports a new experiment documenting a preference for a 1/N rule in portfolio choice in a manner predicted by CST. Section 7 concludes.

2 Salience Theory with Multidimensional Outcomes

To apply salience theory to the two empirical puzzles found in the literature, we first introduce a general salience theory over multidimensional outcomes in which outcomes are grouped into categories.

Let X denote the set of possible outcomes, and let $\Delta(X)$ denote the set of lotteries over X. Let $\succsim$ denote a preference relation on $\Delta(X)$. Under expected utility theory (EU), risk preferences are characterized by the following relationship: For all $L_1, L_2 \in \Delta(X)$,

$$L_1 \succsim L_2 \Longleftrightarrow \sum_{x \in X} L_1(x)u(x) \geq \sum_{x \in X} L_2(x)u(x) \tag{1}$$

where $L_j(x)$ is the probability of receiving outcome x from lottery L_j, and u is a utility function.

Model (1) is the standard model of rational choice under risk. However, a range of empirical tests have documented systematic ways in which observed behavior differs from EU. One recent model developed to explain this empirical evidence is the salience theory of choice under risk from Bordalo et al. (2012). To provide a psychologically grounded explanation of the empirical violations of expected utility theory, Bordalo et al. (2012) propose that a choice between lotteries induces an endogenous state space, and they assume that this state space is the 'minimal state space' that arises if lotteries are statistically independent. They then decompose behavior into two stages. In Stage 1, in accordance with the decision maker's salience perception, the decision maker ranks all pairs of outcomes between two independent lotteries by a salience function, σ. In Stage 2, the decision maker discounts less salient states by a constant discount factor δ, similar to how distant time periods are discounted in models of intertemporal choice.

Formally, let $\dot{\succsim}|_{\mathcal{L}}$ be a 'perceptual' relation over lotteries in choice set $\mathcal{L} := \{L_1, ..., L_n\}$, with the meaning 'looks at least as good as'. Denote the set of all choice sets by Θ. The relation $\dot{\succsim}$ potentially differs from the preference relation $\succsim$ since $\dot{\succsim}$ is influenced by both the preference relation over lotteries, and the 'salience relation' (represented by the salience function) over states. Hence, a decision maker might systematically deviate from preferences in (1) due to the influence of salience perception and instead choose the lottery that 'looks better'. In particular, for a given ranking of salient states, under the Bordalo et al. (2012) salience model, a choice between two lotteries (i.e., $\mathcal{L} := \{L_1, L_2\}$), is represented by:

$$L_1 \dot{\succsim}|_{\mathcal{L}} L_2 \Longleftrightarrow \sum_{s \in S} \delta^s [u(x_s^1) - u(x_s^2)] p_s > 0. \tag{2}$$

In (2), S is the set of salient states induced by choice set $\mathcal{L}$, where the states are ranked by their salience according to a salience function, σ, p_s is the probability that state s occurs, and x_s^j is the outcome in state s if lottery L_j is chosen. If there are k states, the states are ranked such that

$$\sigma(x_1^1, x_1^2) > \sigma(x_2^1, x_2^2) > \cdots \sigma(x_s^1, x_s^2) > \cdots > \sigma(x_k^1, x_k^2). \tag{3}$$

Hence the discount factor δ discounts less salient states exponentially. If $\delta = 1$, then (2) reduces to EU and (1) holds.

Bordalo et al. (2012) demonstrate that (2) can explain a variety of classical anomalies for choices under risk (in particular, the Allais paradox (Allais, 1953), the common ratio effect (Allais, 1953; Kahneman and Tversky, 1979), and the fourfold pattern of risk preferences (Tversky and Kahneman, 1992)), given plausible assumptions about the salience function (that we present in Section 2.2). Of course, although these three anomalies are three of the most robust empirical violations of expected utility theory, they are each explained by alternative models of choices under risk, including prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), disappointment theory (Bell 1985; Loomes and Sugden 1986), and regret theory (Bell 1982; Loomes and Sugden, 1982). To distinguish salience theory from these alternative models, Bordalo et al. (2012) make two additional observations: (i) salience theory predicts the Allais paradox and common ratio effect to be reduced when lotteries are correlated, and (ii) under additional plausible assumptions, salience theory can explain the preference-reversal phenomenon of Lichtenstein and Slovic (1971). Although observations (i) and (ii) are not explained by prospect theory or disappointment theory, they can both be explained by regret theory. Bordalo et al. (2012) thus provide additional discussion suggesting that salience theory provides a better explanation of preference reversals than regret theory. However, as noted, additional assumptions must be applied to salience theory before it can explain preference reversals, and the ability of salience theory to explain (i) and (ii) does not come for free. In particular, (cumulative) prospect theory satisfies both stochastic dominance and transitivity – arguably the two most basic principles of rational choice under risk. Neither of these normative properties is preserved in general by salience theory, although salience theory does preserve stochastic dominance when lotteries are independent (Bordalo et al., 2012). Moreover, the essential property of a salience function – diminishing (absolute) sensitivity, although rooted in psychology, is also at the heart of the prospect theory value function.

In light of the preceding discussion, the question arises as to how salience theory enhances our basic understanding of choices under risk. In this paper, we generalize the Bordalo et al. (2012) salience theory to risky choices involving multidimensional outcomes. We demonstrate that in this larger (and arguably more commonly encountered) choice environment, salience theory generates novel predictions that cannot be explained by any of the conventional models of choice under risk. Moreover, the predictions are strong and systematic – the reverse predictions do not hold. We document empirical puzzles that provide a means of investigating the predictions of this multi-dimensional salience theory, and we observe that salience theory provides a resolution to each of these puzzles.

It has been recently shown by Herweg and Müller (2019) that the Bordalo et al. (2012) salience theory is equivalent to a special case of regret theory (Loomes and Sugden, 1982; Bell, 1982). This correspondence entails that our extension of salience theory developed here can be alternatively interpreted as an extension of regret theory. We feel that our analysis is more naturally motivated by the intuition of salience theory, but one could also develop an alternative interpretation based on regret theory. Consequently, for a single category of outcomes, our model inherits the predictions of salience theory and regret theory. Although both models explain empirical findings that cannot be explained by EU such as the Allais paradoxes and the fourfold pattern of risk preferences, early direct tests of regret theory have identified event-splitting effects that are not predicted by the model (e.g., Starmer and Sugden, 1993). These findings also contradict the Bordalo et al. salience theory. However, more recent direct experimental tests find support for salience theory (Bordalo et al., 2012; Frydman and Mormann, 2018, Nielsen et al., 2018). For instance, Bordalo et al. (2012) and Frydman and Mormann (2018) both observe shifts in the distribution of choices between correlated and statistically independent lotteries in the direction predicted by salience theory.

These findings also support regret theory. As we develop our approach motivated by the intuition of salience theory, we refer to salience theory in the analysis to follow, keeping in mind that in principle, there can be an alternative interpretation based on regret theory.

2.1 Categorical Salience Theory

Choices under risk often involve outcomes that differ in kind (i.e., are from different 'categories'), such as choices between different types of financial investments, different types of consumer goods, or different types of employment opportunities). However, the workhorse framework for studying decisions under risk has been unidimensional monetary lotteries – that is, choices where all outcomes are monetary. It has then been implicitly assumed that behavior for multidimensional lotteries where outcomes differ across categories is not systematically different from behavior for unidimensional monetary lotteries. From a behavioral economics perspective, it is not obvious that this tacit assumption should hold. One general finding in the psychology literature is that people naturally think in terms of categories. Indeed, one author even makes the strong claim that cognition is categorization (Harnad, 2017). It thus seems plausible that, rather than grouping outcomes into salient states, people group outcomes into categories. In particular, our main substantive assumption, and the essence of our approach is to replace the Bordalo et al. (2012) state space and salience ranking across states, and assume instead that people process decisions by aligning outcomes by their categories. We then apply the Bordalo et al. salience theory within categories, resulting in a more general model for multidimensional outcomes that we refer to as 'categorical salience theory' (CST). The CST model links two major concepts from psychology and behavioral economics – categorization and salience perception to decision making, it reduces to the Bordalo et al. salience theory if there is only one category of outcomes, and it provides explanations for two empirical puzzles that violate every standard theory of behavior.

Let outcomes in X be partitioned into C categories. Each category $c \in C$ has $m(c)$ outcomes, and each outcome is included in precisely one category. For each choice set, $\mathcal{L} := \{L_1, ..., L_n\}$, each outcome $i \in c$ and each category $c \in C$, define a category-outcome vector, $\overline{c}_{ic} := (x^1_{ic}, \ldots, x^n_{ic})$ of dimension n. In each $\overline{c}_{ic}$, we let x^j_{ic} denote outcome $i(c)$, $i(c) \in \{1, 2, \ldots, m(c)\}$ from category $c \in C$ that obtains if lottery $L_j \in \mathcal{L}$ is chosen. Risk is modeled as a lottery over category-outcome vectors, where a category-outcome vector is randomly selected for each category $c \in C$. That is, each decision may simultaneously result in multiple outcomes that differ categorically. Indeed, it is rare when a decision in the 'real world' results in only a single isolated outcome. If the decision maker can only choose one lottery from $\mathcal{L}$, then only one outcome in each category-outcome vector (the outcome from the chosen lottery) results from the decision. However, multiple outcomes (one for each category) may still result from the decision. Of course, many categories can have outcomes of zero, where a zero outcome from a category c indicates that nothing is gained or lost in category c as a result of the decision.

We let p_{ic} denote the probability that category-outcome vector $\overline{c}_{ic}$ is the randomly selected vector of outcomes for category c, where $\sum_{i\in c} p_{ic} = 1$ for each $c \in C$. Under Categorical Salience Theory (CST), model (2) is generalized to model[1 2] (4):

$$L_1 \dot{\succsim}|_{\mathcal{C}} L_2 \Longleftrightarrow \sum_{c\in C}\sum_{i\in c} \sigma_c(x_{ic}^1, x_{ic}^2)[u(x_{ic}^1) - u(x_{ic}^2)]p_{ic} > 0. \tag{4}$$

Comparing (2) and (3), we note the following differences: The two stages of generating a salience ranking and then discounting less salient states is merged into a single stage in which the discount factor δ is replaced by the salience function, σ. In this way, salience perception directly distorts how payoff differences are perceived. Outcome differences are summed both within categories and across categories. Bordalo et al. (2012) refer to a decision maker who chooses according to (2) as a *local thinker*. In a similar spirit, we refer to an economic agent who chooses according to (3) as a *categorical thinker*.

For a choice between two independent monetary lotteries, we let the category vectors correspond to the minimal state space in the Bordalo et al. (2012) salience theory (i.e., each pair of outcomes in a category vector corresponds to a 'state' in the Bordalo et al. (2012) minimal state space). In that case, our model of category-dependent risk preferences reduces to the Bordalo et al. (2012) model when there is only one category of outcomes and the one-stage salience weighting in (3) is replaced by the two-stage ranking-then-weighting process assumed by Bordalo et al. (2012). More generally, within any category, we let the category vectors correspond to the minimal state space in Bordalo et al. (2012). Our approach generates novel predictions regarding the relationship between risk preferences for money and for different consumer goods, as well as for deviations from expected utility theory for money and for goods. Both of these predictions have empirical support discussed in Sections 3 and 4, which cannot be explained by expected utility theory with multi-dimensional outcomes (Karni, 1979; DeJarnette, 2017).

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[1] Although model (3) as written applies to binary choice, it can be straightforwardly extended to larger choice sets using an approach such as that suggested in the online appendix to Bordalo et al. (2012).

[2] In general (3) allows for category-dependent salience functions, σ_c which may be natural when comparing outcomes across categories that have different units (such as the weight of a bag of potato chips versus the price of the bag). This generality will not be necessary in our subsequent analysis. To constrain the model, we use a category-independent salience function and we accordingly drop the c subscript in what follows.

2.2 Extension to Multiple Alternatives

Representation (4) can be extended from a model of binary choice to simultaneous choice among multiple alternatives. A simple approach is for a categorical thinker to evaluate a lottery L_k from choice set $\mathcal{L}$ as in (5)

$$\mathrm{V}(L_k|\mathcal{L}) = \frac{1}{n}\sum_{L_j \in \mathcal{L}}\sum_{c \in C}\sum_{i \in c}\sigma_c(x_{ic}^k, x_{ic}^j)[u(x_{ic}^k) - u(x_{ic}^j)]p_{ic} \tag{5}$$

Under (5), a categorical thinker evaluates each lottery according to the salient comparisons of that lottery's payoffs with the background context (the other alternatives in the choice set). Formula (5) computes salient comparisons across outcomes, across categories, and across lotteries. When the choice set contains only two alternatives, (5) is equivalent to (4).

2.3 Properties of Salience Perception

The salience function, σ, is assumed to satisfy two basic properties: (i) ordering and (ii) diminishing absolute sensitivity. Ordering implies that the perceptual system is more sensitive to larger differences in outcomes when the outcomes with the smaller difference are contained in the interval spanned by the outcomes with the larger difference. Diminishing Absolute Sensitivity (DAS) implies that for a fixed absolute difference, the perceptual system is more sensitive to larger ratios. The DAS property is rooted in the Weber-Fechner law in psychology. Bordalo et al. (2012) justify this assumption in their salience model, noting "As in Weber's law of diminishing sensitivity, in which a change in luminosity is perceived less intensely if it occurs at a higher luminosity level, the local thinker perceives less intensely payoff differences occurring at high (absolute) payoff levels" (p. 1254). Citing evidence from McCoy and Platt (2005), Bordalo et al. add that "visual perception and risk taking seem to be connected at a more fundamental neurological level" (p. 1254-1255). In the appendix we show one way that this intuition can be made more precise.

The DAS property of salience perception has also been used in models of salience-based choice to explain ambiguity aversion (Leland, Schneider, & Wilcox, 2019), present bias (Prelec and Loewenstein, 1991), and an attraction to consumer products with high quality-price ratios (Bordalo et al., 2013a). We employ the following definition based on Bordalo et al. (2012, 2013a):

Definition 1: (Salience Function): A non-negative, continuous, symmetric and bounded function, $\sigma(x_{ic}^1, x_{ic}^2)$ is a *salience function* if the following two properties hold:

1. **Ordering:** If $[x_{ic}^1, x_{ic}^2] \subset [x_{ic}^{1'}, x_{ic}^{2'}]$, then $\sigma(x_{ic}^1, x_{ic}^2) < \sigma(x_{ic}^{1'}, x_{ic}^{2'})$.

2. **Diminishing Absolute Sensitivity (DAS):** For all $x_{ic}^{j} > 0, \epsilon > 0$, and for all $L_j \in \mathcal{L}$, $\sigma(x_{ic}^{1} + \epsilon, x_{ic}^{2} + \epsilon) < \sigma(x_{ic}^{1}, x_{ic}^{2})$.

One other property of salience perception that is natural to assume is the following:

Increasing Proportional Sensitivity (IPS): For all $x_{ic}^{j} > 0, \alpha > 1, x_{ic}^{1} \neq x_{ic}^{2}$ and for all $L_j \in \mathcal{L}, \sigma(\alpha x_{ic}^{1}, \alpha x_{ic}^{2}) > \sigma(x_{ic}^{1}, x_{ic}^{2})$.

Increasing Proportional Sensitivity (IPS) implies that for a fixed ratio, the perceptual system is more sensitive to larger absolute differences. The IPS property was explicitly assumed by Prelec and Loewenstein (1991) for the perception of payoffs, probabilities, and time delays and it generates a preference for positively skewed lotteries when applied to the Bordalo et al. (2012) salience theory. It has also received empirical support in the marketing literature by Pandelaere et al. (2011) and Wertenbroch (2007) who observe IPS for numerical and monetary stimuli. More broadly, IPS generates one of the central implications of salience theory – a preference for positively skewed lotteries. A preference for positive skewness (attraction to low-probability, low-cost, high-payoff lotteries) can explain the popularity of state-run lotteries, the favorite-longshot bias in race-track betting (Golec and Tamarkin, 1998), the over-valuation of IPO's, growth stocks, and other positively skewed financial assets (Barberis and Huang, 2008; Bordalo et al., 2013b), and the motivation for bargain hunting on eBay. However, the determinants of skewness preference are not well understood. Salience theory provides a psychologically grounded account of skewness preference in decision making. Moreover, using simple perceptual decision tasks, Rochanahastin et al. (2018) provide experimental evidence indicating that visual perception satisfies IPS. Interestingly, they also find that experimental participants who more frequently violated IPS in the perceptual task, were also significantly less likely to select positively skewed lotteries in a subsequent decision task, suggesting a link between visual perception and risky choice. Such a link is consistent with the hypothesis used by McCoy and Platt (2005) to explain their data that "enhanced neuronal activity associated with risky rewards biases attention spatially, marking large payoffs as salient for guiding behavior" (p. 1226). Although we state DAS and IPS as natural assumptions of salience perception supported by both the psychology and decision theory literature, our proofs in Sections 3 and 4 rely only on the ordering property of salience perception which implies, for instance, that the comparison between payoffs of \$40 and \$60 is less salient than the comparison between \$1 and \$100.

Bordalo et al. (2012) proposed the following salience function that satisfies ordering, DAS, and IPS, where $\theta > 0$:

$$\sigma(x_{ic}^{1}, x_{ic}^{2}) = \frac{|x_{ic}^{1} - x_{ic}^{2}|}{|x_{ic}^{1}| + |x_{ic}^{2}| + \theta}. \tag{6}$$

In their analysis of consumer choice, Bordalo et al. (2013a) proposed a parameter-free variant of (6) in which the salience function is defined as in (6) with $\theta = 0$, and to ensure the function is well-defined, they set $\sigma(0, 0) = 0$. To explain the fourfold pattern of risk preferences and skewness preference more generally, the parameter θ must be positive. However, since (i) θ does not have an intuitive psychological or economic interpretation, and (ii) since the predictions of salience theory appear to be largely insensitive to variations in θ for a wide range of parameter values, all of our analyses that employ a specific salience function will employ (6) with $\theta = 1$ to illustrate the model.

We do not impose IPS as a required property of all salience functions since Bordalo et al. (2013a) employ a salience function that does not satisfy IPS in their analysis of consumer choice. By not imposing IPS, our assumptions are consistent with theirs. However, in illustrating our approach, we employ salience function (6) which does satisfy IPS, thereby retaining the prediction of skewness preference that is a central implication of salience theory.

In addition to satisfying ordering, DAS, and IPS, salience function (6) has another psychological foundation. In particular, in the appendix, we show that this measure of contrast between two payoffs in a choice set coincides with a formula that has been used in computational neuroscience to measure visual contrast between two pixels in an image (e.g., Raj et al., 2005; Frazor and Geisler, 2006; Chen and Blum, 2009).

3 Lotteries over Multidimensional Outcomes

In this section we apply CST to choices between lotteries over multidimensional outcomes. In sections 3.1 and 3.2 we show how CST can explain existing empirical anomalies. In section 3.3, we conduct a new experiment that was designed to test an additional prediction of CST.

3.1 Risk Preferences over Money versus Goods

One recent puzzle regarding risk preferences was identified by DeJarnette (2017). In his experiment, subjects allocated either monetary credit or an equivalent value of goods from Amazon.com over equally likely states (either two states, over which \$20 was allocated, or ten states, over which \$100 was allocated). Subjects allocating monetary credit were required to spend their money on consumer goods at Amazon.com prior to leaving the laboratory. DeJarnette observed significantly more risk aversion over money than over goods. For instance, subjects were more likely to allocate money equally across states and to allocate a high-value consumer good to one of the states. DeJarnette did not provide an explanation for his findings but demonstrated that standard approaches could not explain his results.

The categorical salience model in (4) offers a novel approach to DeJarnette's puzzle. Since money is a single 'category', choices involving money are represented as in the 'Money Frame' in Figure I. Since consumer goods typically span many different product categories, if products are aligned by their categories, then these choices are represented as in the 'Consumer Goods Frame' in Figure I.

Money Frame

	$	$
	Heads	Tails
p	0.5	0.5
A	15	5
B	**10**	**10**

Consumer Goods Frame

	Good 1	Good 1	Good 2	Good 2	Good 3	Good 3
	Heads	Tails	Heads	Tails	Head	Tails
p	0.5	0.5	0.5	0.5	0.5	0.5
A′	**15**	**0**	**0**	**5**	**0**	**0**
B′	0	0	0	0	10	10

Figure I. Risk Preferences over Money versus Goods

Consider the case in which a consumer chooses between two bets on the toss of a coin. In bet A, the consumer receives $15 if the coin lands heads and $5 if the coin lands tails. In bet B, the consumer receives $10 regardless of whether the coin lands heads or tails. Formally, for this 'money frame', we have $\mathcal{L} := \{L_1 = \mathrm{A}, L_2 = \mathrm{B}\}$, $j \in \{1, 2\}, c \in \{1\}, i \in \{1, 2\}$. The category-outcome vectors are:

$$\bar{\mathrm{c}}_{11} := \{x_{11}^1, x_{11}^2\} = \{15, 10\}, \bar{\mathrm{c}}_{21} := \{x_{21}^1, x_{21}^2\} = \{5, 10\}.$$

As there is only a single category, the probabilities are given by $(p_{11}, p_{21}) = (0.5, 0.5)$.

Consider next the case in which a consumer chooses between a different pair of bets on the toss of a coin. In bet A', the consumer receives 'good 1' that is worth $15 to him if the coin lands heads and he receives a good that he values at $5 (good 2) if the coin lands tails. In bet B', the consumer receives a good that he values at $10 (good 3) regardless of the outcome of the coin toss. Formally, for this 'consumer goods frame', we have $\mathcal{L} := \{L_1 = \mathrm{A}', L_2 = \mathrm{B}'\}$, $j \in \{1, 2\}, c \in \{1, 2, 3\}, i \in \{1, 2\}$. That is, there are three (goods) categories. The category-outcome vectors are:

$$\bar{\mathrm{c}}_{11} := \{x_{11}^1, x_{11}^2\} = \{15, 0\}, \bar{\mathrm{c}}_{12} := \{x_{12}^1, x_{12}^2\} = \{0, 0\}, \bar{\mathrm{c}}_{13} := \{x_{13}^1, x_{13}^2\} = \{0, 10\},$$

$$\bar{c}_{21} := \{x_{21}^1, x_{21}^2\} = \{0, 0\}, \bar{c}_{22} := \{x_{22}^1, x_{22}^2\} = \{5, 0\}, \bar{c}_{23} := \{x_{22}^1, x_{22}^2\} = \{0, 10\}.$$

The probabilities for these category outcome vectors are $(p_{11}, p_{21}, p_{12}, p_{22}, p_{13}, p_{23}) =$ (0.5,0.5,0.5,0.5,0.5,0.5). Since outcomes are aligned by their categories, they are not directly compared if they are in different categories. That is, receiving the \$10 good is compared to not receiving the \$10 good (a payoff of \$0), rather than being compared to receiving the \$15 good or the \$5 good.

Under our running specification (where $u(x) = x$, and σ is given by (4) with $\theta = 1$), the CST model predicts that a categorical thinker allocates money evenly across states (due to the DAS property of salience), but prefers to allocate goods asymmetrically due to the ordering property of salience (e.g., a \$15 item in one state and a \$5 item in another state is preferred to allocating a \$10 item to each state)[3]. Lotteries B and A' are bolded in Figure I because they are the CST preferred lotteries. We follow the convention of bolding the CST preferred option throughout the remainder of the paper.

	Money Frame	
	\$	\$
p	0.5	0.5
A	x	0
B	$\boldsymbol{y}$	$\boldsymbol{y}$

	Consumer Goods Frame		
	Good 1	Good 1	Good 2
p	0.5	0.5	1
A′	$\boldsymbol{x}$	**0**	**0**
B′	0	0	y

Figure II. Risk Preferences with Payoffs Aligned by their Categories

For the choice between lotteries A and B over money in Figure II, the category outcome-vectors are $c_1 := (x, y)$ and $c_2 := (0, y)$. For the choice between lotteries A' and B' over consumer goods in Figure II, the category outcome vectors are $c_{11} := (x, 0)$, $c_{21} := (0, 0)$, $c_{12} := (0, y)$. The probabilities for these category outcome vectors are $(p_{11}, p_{21}, p_{12}) = (0.5, 0.5, 1)$.

Definition 2: For the choices in Figure II, a categorical thinker exhibits *more risk aversion toward money than toward different goods* if $\mathrm{A} \dot{\sim}|_{\{\mathrm{A},\mathrm{B}\}}\mathrm{B}$ implies $\mathrm{A}' \dot{\succ} |_{\{\mathrm{A}',\mathrm{B}'\}}\mathrm{B}'$.

Proposition 1: *For the choices in Figure II, let $x > y \geq 0.5x$ and let $u(x) = x$. Then a categorical thinker exhibits more risk aversion toward money than toward different goods.*

[3] For the money frame in Figure I, $\mathrm{B}\dot{\succsim}|_{\mathcal{L}}\mathrm{A}$ as $\frac{|15-10|}{|15|+|10|+1}(15 - 10)(0.5) + \frac{|5-10|}{|5|+|10|+1}(5 - 10)(0.5) < 0$. For the goods frame in Figure I, $\mathrm{A}'\dot{\succsim}|_{\mathcal{L}}\mathrm{B}'$ as $\left[\frac{|15-0|}{|15|+|0|+1}(15-0)(0.5) + \frac{|0-0|}{|0|+|0|+1}(0-0)(0.5)\right] + \left[\frac{|0-0|}{|0|+|0|+1}(0-0)(0.5) + \frac{|5-0|}{|5|+|0|+1}(5-0)(0.5)\right] + \left[\frac{|0-10|}{|0|+|10|+1}(0-10)(0.5) + \frac{|0-10|}{|0|+|10|+1}(0-10)(0.5)\right] > 0$.

Proof: For the choice of A versus B, $\mathrm{A} \dot{\sim}|_{\{\mathrm{A},\mathrm{B}\}} \mathrm{B}$ if and only if

$$\sigma(0,y)[-y]0.5+\sigma(x,y)[x-y]0.5=0.$$

For the choice of A′ versus B′, $\mathrm{A}' \dot{\succ}|_{\{\mathrm{A}',\mathrm{B}'\}} \mathrm{B}'$ if and only if

$$\sigma(x,0)[x]0.5>\sigma(0,y)[y].$$

Substituting $\sigma(0,y)[y]=\sigma(x,y)[x-y]$, we have $\mathrm{A}' \dot{\succ}|_{\{\mathrm{A}',\mathrm{B}'\}} \mathrm{B}'$ if and only if $\sigma(x,0)[x]0.5>\sigma(x,y)[x-y]$. Let $y=0.5x$. Then $\mathrm{A}' \dot{\succ}|_{\{\mathrm{A}',\mathrm{B}'\}} \mathrm{B}'$ if and only if $\sigma(x,0)[x]0.5>\sigma(x,0.5x)[0.5x]$ which holds by ordering. For $y>0.5x$, ordering implies $\sigma(x,0.5x)[0.5x]>\sigma(x,y)[x-y]$. □

3.2 The Common Ratio Effect for Money versus Goods

The categorical salience model in (3) also makes novel predictions for the classical common ratio effect in choices under risk. The common ratio effect (Allais, 1953) is one of the best-known and most robust systematic violations of expected utility theory. However, empirical studies of the common ratio effect have traditionally used money as the outcome. If the outcomes are consumer goods in different categories, the CST predicts that the common ratio effect will disappear.

The common ratio effect consists of a pair of choices that are related because the probabilities of prizes in the second choice scale down the probabilities of the same prizes in the first choice by a common ratio. In both versions of the common ratio effect in the top portion of Figure III, one alternative yields an 80% chance of winning a \$4z prize (Option A), either in cash or in the form of a consumer good that the decision maker values at \$4z, for some constant z > 0, and the other alternative yields \$3z with certainty (Option B). In the bottom portion of Figure III, the decision maker chooses between a 20% chance of the same \$4z prize in Choice 1 (Option C) and a 25% chance of winning the \$3z prize from Choice 1 (Option D).

A decision maker exhibits the common ratio effect by choosing 3z with certainty over an 80% chance of 4z, and also choosing a 20% chance of 4z over a 25% chance of 3z. This pattern of behavior violates EU and explaining it has been one of the primary motivations behind alternative theories of choice under risk.

'Money Frame'

	$	$
p	0.80	0.20
A	$4z$	0
B	$\mathbf{3z}$	$\mathbf{3z}$

'Consumer Goods' Frame

	Good 1	Good 1	Good 2
p	0.80	0.20	1
$\mathbf{A'}$	$\mathbf{4z}$	**0**	**0**
B'	0	0	$3z$

	$	$	$	$
p	0.05	0.15	0.20	0.60
C	$\mathbf{4z}$	$\mathbf{4z}$	**0**	**0**
D	$3z$	0	$3z$	0

	Good 1	Good 1	Good 2	Good 2
p	0.20	0.80	0.25	0.75
$\mathbf{C'}$	$\mathbf{4z}$	**0**	**0**	**0**
D'	0	0	$3z$	0

Figure III. The Common Ratio Effect with Payoffs Aligned by their Categories

Figure III displays the category outcome vectors for the common ratio lotteries, along with the probability that each category outcome vector is randomly selected. For the money frame in Figure III, these probabilities correspond to the state probabilities in the minimal state space of the Bordalo et al. (2012) model given that the lotteries are statistically independent. Bordalo et al. (2012, p.1254) note that the minimal state space can be identified "by the set of distinct payoff combinations that occur with positive probability." They note that for statistically independent lotteries, the minimal state space is the product space induced by the lotteries' marginal distributions over payoffs. Importantly, the minimal state space is uniquely defined and so leaves no degrees of freedom for how probabilities are assigned. For instance, in the choice between options C and D in Figure III, the minimal state space assigns probability 0.05 (0.20×0.25) to category-outcome vector (4z, 3z), probability 0.15 (0.20×0.75) to category-outcome vector (4z, 0), probability 0.20 (0.25×0.80) to category-outcome vector (0, 3z), and probability 0.60 (0.75×0.80) to category-outcome vector (0, 0).

In the money frame, the outcomes are in a single category (money). In the consumer goods frame, the outcomes span two product categories (Good 1 and Good 2). Since outcomes are aligned by their categories in (3), the comparison between a payoff worth 4z and a payoff worth 3z is not cued in the choice between A' and B' since these outcomes are in different categories. As a consequence, the 4z payoff from Good 1 under lottery A' is compared to a zero payoff from not receiving Good 1 under lottery B'. Since the category-outcome vector (4z,0) is salient in both choice sets {A', B'} and {C', D'}, the CST model in (3) predicts consistent choices of A' over B' and C' over D' for lotteries over consumer goods. In contrast, since the category-outcome vector (0,3z) that favors B is salient in choice set {A,B} and the category-outcome vector (4z,0) that favors C is salient in choice set {C,D}, CST predicts the decision maker will exhibit the common ratio effect in the money frame. Hence, CST predicts the classical common ratio effect in the money frame but predicts consistent risk preferences in the consumer goods frame.

Under EU from (1), a decision maker is predicted to exhibit consistent risk preferences for both money and equally valued goods. In addition, salience theory from (2) aligns outcomes by salient states rather than by categories. Since both the money lotteries and the consumer goods lotteries in each choice set are statistically independent, salience theory predicts that both choices are framed as in the 'money frame' in Figure III. Hence, salience theory predicts that a decision maker displays the same behavior under risk toward money as toward goods.

Recently, Arroyos-Calvera et al. (2018) tested the common ratio effect with money and consumer goods in an incentivized experiment. They used 10 objects for the goods and elicited subject valuations for each object. To test the common ratio effect with goods, they presented subjects with pairs of goods such that their valuations approximately preserved the 3:4 ratio of the monetary prizes that has also been used in the classical common ratio experiments (e.g., Kahneman and Tversky, 1979). They report, "we manipulated object similarity by using some pairs of goods that had common characteristics (alarm clocks with different additional features), and other pairs where the characteristics were rather different and more difficult to compare (such as an airbed and a toaster, or an alarm clock and a suitcase.)" (p. 3). They observed the standard common ratio effect for monetary consequences but note that it was significantly weakened for similar goods and that it disappeared for dissimilar goods. Each of these findings is in line with the predictions of the CST: The common ratio effect was strongest in the money frame, it disappeared in the frame where the goods were clearly in different categories, and it was weakened but present for similar goods, which plausibly some subjects categorized as different and some classified in the same category.

Note that CST not only predicts the common ratio effect will disappear when the items are in different categories, it predicts this to happen in a particular direction: choices are predicted to shift toward the riskier lottery in the choice with a certain outcome. As predicted by CST, Arroyos-Calvera et al. (2018) report, "The stronger tendency for people to choose the risky alternative in the scaled up questions with goods may be at least partially driving this." (p.3)[4]. Formally, we have the following definition and result:

[4]Under the assumption that the Bordalo et al. (2012) minimal state space holds within categories, CST

Definition 3: Consider the four lotteries in Figure IV[5]: A $:= (x, p; 0, 1-p)$, B $:= (y,1)$, A$' := (x, rp; 0, 1-rp)$, B$' := (y, r; 0, 1-r)$, where $r \in (0,1)$ and $\mathbb{E}[\mathrm{A}] \geq \mathbb{E}[\mathrm{B}]$. A categorical thinker exhibits the *common ratio effect* if A $\dot{\sim}|_{\{\mathrm{A,B}\}}$B implies A$'$ $\dot{\succ}|_{\{\mathrm{A',B'}\}}B'$.

Proposition 2: *Let $\sigma(0,0) = 0$ and $u(x) = x$. Then for the common ratio lotteries (shown in Figure IV), a categorical thinker exhibits the common ratio effect for money, but does not exhibit the common ratio effect for choices over goods in different categories.*

Proof: For the choice of A versus B in the money frame (shown in Figure IV), A $\dot{\sim}|_{\{\mathrm{A,B}\}}$B if and only if $\sigma(0, y)[-y](1-p) + \sigma(x, y)[x-y]p = 0$.

For the choice of A$'$ versus B$'$ in the money frame, A$'$ $\dot{\succ}|_{\{\mathrm{A',B'}\}}B'$ if and only if

$$\sigma(x, y)[x-y](r^2p) + \sigma(x,0)[x](rp - r^2p) > \sigma(0, y)[y](r - r^2p).$$

Substituting $\sigma(x, y)[x-y]p = \sigma(0, y)[-y](1-p)$, A$'$ $\dot{\succ}|_{\{\mathrm{A',B'}\}}B'$ if and only if

$$\sigma(0, y)[y](1-p)r + \sigma(x,0)[x](p - rp) > \sigma(0, y)[y](1 - rp),$$

which holds if and only if $\sigma(x,0)[x]p > \sigma(0, y)[y]$. Since $\mathbb{E}[\mathrm{A}] \geq \mathbb{E}[\mathrm{B}]$, by ordering of σ, the categorical thinker exhibits the common ratio effect for money.

For the choice of A versus B in the consumer goods frame (shown in Figure IV), A $\dot{\sim}|_{\{\mathrm{A,B}\}}$B if and only if $\sigma(x,0)[x]p = \sigma(0, y)[y]$ which cannot hold due to the ordering property of σ and since E[A] $\geq \mathbb{E}[\mathrm{B}]$. Instead, we have $\sigma(x,0)[x]p > \sigma(0, y)[y]$ which implies both A $\dot{\succ}|_{\{\mathrm{A,B}\}}$B and A$'$ $\dot{\succ}|_{\{\mathrm{A',B'}\}}B'$ and thus the categorical thinker does not exhibit the common ratio effect for goods in different categories. □

It is also the case more generally (i.e., for any utility function) that the common ratio effect does not hold for consumer goods in different categories and instead a categorical thinker conforms to expected utility theory over goods, as observed by Arroyos-Calvera et al. (2018). While it is the case that a sufficiently concave utility function could produce consistent risk-averse choices over goods, the salient comparison that drives this choice favors the riskier lottery which will produce a systematic bias toward that lottery, relative to the

does not explain all features of the experiment by Arroyos-Calvera et al. (2018). In particular, they find greater risk-seeking for the choice between C and D in Figure III than for the choice between C$'$ and D$'$. However, CST predicts that a consumer indifferent between C and D would choose C$'$ over D$'$. If one instead develops CST assuming that choice are represented by minimal frames within categories as formalized in Leland et al. (2019) and employs their salience weighted utility model that operates over frames, then CST predicts greater risk-seeking in the choice between C and D than in the choice between C$'$ and D$'$. That approach preserves the other predictions in this paper. However, to deviate as little as possible from the standard salience theory of Bordalo et al. (2012), we assume choices are represented by (4) and that choices within categories are represented by the minimal state space.

[5]The minimal state space for the choice between A' and B' over monetary outcomes in Figure IV uniquely assigns probability r^2p ($rp \times r$) to category-outcome vector (x, y), probability $rp(1-r)$ ($rp \times (1-r)$) to category-outcome vector $(x, 0)$, probability $r(1-rp)$ ($r \times (1-rp)$) to category-outcome vector $(0, y)$, and probability $(1-rp)(1-r)$ ($(1-rp) \times (1-r)$) to category-outcome vector $(0, 0)$.

true risk preferences of the categorical thinker (in the absence of salience distortions).[6]

'Money Frame'

	\$ p	\$ $1-p$
A	x	0
B	$\boldsymbol{y}$	$\boldsymbol{y}$

'Consumer Goods' Frame

	Good 1 p	Good 1 $1-p$	Good 2 1
A	$\boldsymbol{x}$	**0**	**0**
B	0	0	y

	\$ r^2p	\$ $rp(1 - r)$	\$ $r(1 - rp)$	\$ $(1-rp)(1-r)$
$\mathbf{A'}$	$\boldsymbol{x}$	$\boldsymbol{x}$	**0**	**0**
B'	y	0	y	0

	Good 1 rp	Good 1 $1-rp$	Good 2 r	Good 2 $1-r$
$\mathbf{A'}$	$\boldsymbol{x}$	**0**	**0**	**0**
B'	0	0	y	0

Figure IV. The Common Ratio Effect with Payoffs Aligned by their Categories

3.3 Experiment on Risk Preferences Across Categories

To further investigate the predictions of CST, we conducted an experiment involving tradeoffs within categories and across categories. One hundred and fifty four subjects participated: fifty-eight participants were female and ninety-six were male.[7] All subjects were individuals on The University of Alabama campus who passed by a rolling cart that we arranged with four types of snacks: a regular size pack of m & m's, a pack of six Oreo cookies, a small bag of Lay's potato chips, and a pack of Cheez-it crackers. The options were chosen to represent different categories of snacks (chocolate, cookies, potato chips, crackers), and to increase the likelihood that there would be two snacks that a subject liked. The sample size was

[6] A general statement that categorical salience theory satisfies the independence axiom is not possible since the perceptual relation is choice set dependent. The categorical thinker prefers A to B if and only if they prefer A' to B', regardless of whether $\mathbb{E}[\mathrm{A}] \geq \mathbb{E}[\mathrm{B}]$ or not, where these values are as given in Definition 3. To see this, note A $\dot{\succ}|_{\{\mathrm{A,B}\}}B\Longleftrightarrow \sigma(x,0)[x]p = \sigma(0,y)[y] \Longleftrightarrow r\sigma(x,0)[x]p = r\sigma(0,y)[y] \Longleftrightarrow A' \dot{\succ}|_{\{\mathrm{A',B'}\}}B'$.

[7] We made no attempt to recruit more males than females. The discrepancy between the number of male and female participants might reflect that the female participants we asked to participate declined more frequently than the male participants.

determined so as to yield 80% power for identifying an effect at the 5% significance level for a one-tailed test[8] under the prior that the true proportion of risky cross-category choices is 60% and the true proportion of risky within-category choices is 40%.

We employed a between-subjects design with two treatments. Subjects made a single choice between two lotteries over snacks. In the *within-category* treatment, subjects chose between a safe (S) lottery offering a 9/10 chance of one unit of a snack and a riskier (R) lottery offering a 5/10 chance of 2 units of the same snack. In the *cross-category* treatment, subjects chose between an S lottery offering a 9/10 chance of one unit of a snack and a R lottery offering a 5/10 chance of 2 units of a different snack. The probabilities were chosen so that they could be transparently presented and implemented with a ten-sided die.

Assignment to treatment was alternated.[9] For within-category choices, we first asked subjects to identify their favorite snack out of the four snack choices available. For cross-category choices, we first asked subjects to identify their two favorite types of snacks. Subjects were informed that their compensation would be in snacks so that they had an incentive to truthfully reveal their preferences. For the cross-category choices we randomized between using the snack the subject picked first as the safe lottery and using the snack the subject picked first for the riskier lottery. This randomization was done prior to data collection so that we knew which condition to implement and could do so efficiently as potential participants approached the rolling cart.[10]

Representations for the choices in the experiment under CST are uniquely determined by the minimal state space and are shown in Figure V[11]. In the figure, there are two snacks, where one unit of each snack brings a utility of 1 and 2 units of each snack brings a utility of 2. For these choices, CST (as specified in equations (4) and (6) with $\theta = 1$) predicts subjects will exhibit greater risk aversion in the within-category treatment than in the cross-category treatment. In particular, CST predicts that the comparison of getting two units in the cross-category choice will be more salient than the comparison of getting two units in the

[8]The one-tailed test is the appropriate statistical test since CST makes clear directional predictions of greater risk tolerance in cross-category choices and a difference in the opposite direction would not support CST.

[9]If a subject approached the rolling cart while the previous subject was present the same treatment was applied so as to avoid confusion and to mask the purpose of the experiment. However, an equal number of subjects participated in each treatment.

[10]One researcher administered the experiment while another recorded the data which included the treatment, whether the subject chose to go for 1 snack with a 90% chance (safe lottery) or 2 snacks with a 50% chance (risky lottery), and the subject's sex (male or female).

[11]The minimal state space for the within-category choices in Figure V uniquely assigns probability 0.45 (0.90×0.50) to category-outcome vector $(1, 2)$, probability 0.45 (0.90×0.50) to category-outcome vector (1, 0), probability 0.05 (0.10×0.50) to category-outcome vector (0, 2), and probability 0.05 (0.10×0.50) to category-outcome vector (0, 0).

within-category choice (since $0.5\sigma(0,2) > 0.45\sigma(1,2) + 0.05\sigma(0,2)$).[12] Under our running parametric specification, the safe (S) lottery is chosen in the within-category choice, but the risky (R) lottery is chosen in the cross-category choice. Hence, CST predicts a shift toward greater risk-taking in the cross-category choices.

Within-Category Choice

	Snack A			
p	0.45	0.45	0.05	0.05
Safe	1	1	0	0
Risky	2	0	2	0

Cross-Category Choice

	Snack A		Snack B	
p	0.90	0.10	0.50	0.50
Safe	1	0	0	0
Risky	0	0	2	0

Figure V. Risky Choices Within and Across Categories

We find that 62.3% of the subjects in the within-category treatment selected the S lottery indicating a typical level of risk aversion. However, 46.8% of the subjects in the cross-category treatment opted for the S lottery. Thus, observed behavior shifts in the direction predicted by CST and the difference is statistically significant ($p = 0.02619$, one tailed two-sample proportions test).

The results are summarized in Table I. The first row displays the percentage of R lottery choices in the within-category treatment. The second row displays the percentage for R lottery choices in the cross-category treatment.

	Total (% R)
Within-Category	0.377
Cross-Category	0.532

Table I. Proportion of Risky Choices Across Treatments

[12] One caveat is that this prediction is derived under the assumption that the two snacks are valued equally. While the prediction continues to hold if the snacks are valued approximately equally, it need not hold if there is a strong preference for one snack over the other. For this reason we selected four types of snacks and asked participants to pick their favorite two for the cross-category choices, supposing that more snacks to choose from increases the chances that subjects would find multiple snacks they liked. We also selected the snacks to be comparable in retail value.

4 Categorization and Portfolio Choice

We next consider implications of CST for the use of diversification strategies in consumer choice and portfolio choice.

4.1 Variety-Seeking in Simultaneous versus Sequential Choice

One of the more puzzling anomalies in the consumer behavior literature is the diversification bias: Simonson (1990) and Read and Loewenstein (1995) both find greater variety seeking behavior in simultaneous than in sequential choices. In of their experiments, Read and Loewenstein tested this behavior on Halloween night. Children trick-or-treating between two adjacent houses were either given a single choice between a milky way candy bar and a musketeers bar at each house (sequential choice condition), or a choice of two candy bars (which could be two milky way, two musketeers, or one of each) at one of the houses (simultaneous choice condition). Read and Loewenstein found that in the simultaneous choice condition, all children chose one of each candy bar, whereas only 48% of children in the sequential choice condition did so.

The puzzling choices observed by Read and Loewenstein can be simply reconciled by CST. Figure VIII depicts the CST representation of these choices in the simultaneous and sequential choice conditions. Note that in the simultaneous choice, diminishing sensitivity implies that the downside of not obtaining any of one candy outweighs the upside of obtaining two of the other candy. Hence, CST implies the use of the diversification heuristic in the simultaneous choice for any salience function. In the sequential choice, if the two bars have roughly the same utility, CST predicts indifference in these choices. Indeed, the finding that 48% of the children chose one of each candy in the sequential choice is consistent with the implication of CST that the children were indifferent in the sequential choices and chose randomly.

Greater Variety Seeking in Simultaneous than in Sequential Choice

	Simultaneous Choice			**Sequential Choice 1**			**Sequential Choice 2**	
	Candy A	Candy B		Candy A	Candy B		Candy A	Candy B
Option 1	1	1	Option 1	1	0	Option 1	1	0
Option 2	2	0	Option 2	0	1	Option 2	0	1

Figure VIII. The Diversification Heuristic

A CST agent with $u(x) = x$ chooses one of each item in the simultaneous choice but is indifferent between each item in the sequential choices in Figure VIII if the following inequality holds:

$$\sigma(1,0) - \sigma(1,2) > 0.$$

The above inequality follows generally from diminishing sensitivity and symmetry of σ. Hence, the CST agent chooses to diversify in the simultaneous choice, and chooses randomly in the sequential choice, consistent with the findings of Read and Loewenstein.

4.2 The "1/N" Rule in Portfolio Choice

Benartzi and Thaler (2001) find evidence consistent with a 1/N diversification heuristic in portfolio allocation decisions. Under this heuristic, given a fixed amount of money to allocate to N different assets, a significant fraction of people allocate an equal amount to each asset. This form of diversification can deviate from a truly diversified portfolio as we illustrate below.

The CST model also generates a novel prediction for portfolio choice - that behavioral investors will systematically deviate from allocating an equal amount of resources *across states*, by instead allocating an equal amount of resources *across categories*. The CST thus provides a formal framework for contrasting the predictions of expected utility theory with those of the diversification heuristic.

Naive diversification is an empirical puzzle for both leading rational and behavioral decision theories of choice under risk. In independent work, Koszegi and Matejka (2019) developed a model of choice simplification and Landry and Webb (2020) developed a neuroeconomic model of multi-attribute choice, both of which generate behavior consistent with the diversification heuristic. However, these models were not developed as general models of choice under risk and so do not explain our other findings or the classical risky choice anomalies such as the fourfold pattern of risk preferences (Tversky and Kahneman, 1992).

4.2.1 Experiment on Diversification across Categories versus States

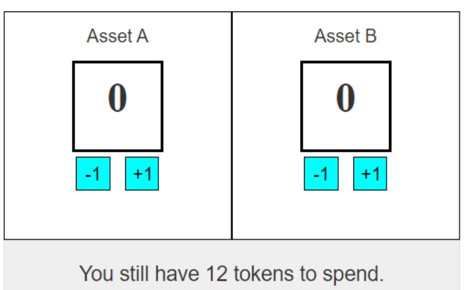
We conducted an online experiment using Amazon Mechanical Turk[13] to explore the competing predictions of true diversification implied by EU for any risk-averse agent with 'naive' diversification implied by CST for the same investment decision. Experimental subjects each

[13]We used a lab-in-the-field procedure for the risky choices across categories experiment given the complexity of delivering non-monetary payments in an online experiment.

participated in one portfolio allocation decision, involving either two states and two categories or three states and three categories. In the two-state, two-category decision[14], subjects were asked to allocate 12 tokens across two different assets, where each asset yields a payoff in one of two equally likely states. In particular, subjects were shown the table on the left side of Figure IX. Subjects were informed that each experimental currency unit (ECU) was worth \$0.05. That is, if Outcome 1 occurred and all 12 tokens were allocated to Asset B, that subject would earn 36 ECU's (\$1.80).[15] To allocate their tokens, subjects were required to increase or decrease their allocation to each asset by changing one token at a time, with the initial allocation set to 0. The experimental software enforced the requirement that exactly 12 tokens must be allocated before that subject could proceed. In the three-asset, three-state portfolio decision, a different group of subjects was asked to allocate 15 tokens across three different assets, where each asset yields a payoff in one of three equally likely states. In particular, subjects were shown the table on the right side of Figure IX. For simplicity, we refer to Asset A as shown in the figure as the "safe" asset in both conditions, and Asset B as shown in the figure as the "risky" asset in both conditions, but this terminology was not used with the subjects. The actual order of the rows and columns were randomized across subjects in both conditions.

	Outcome 1	Outcome 2
Asset A	1 ECU	2 ECUs
Asset B	3 ECUs	0 ECU

	Outcome 1	Outcome 2	Outcome 3
Asset A	1 ECU	2 ECUs	3 ECUs
Asset B	6 ECUs	0 ECU	0 ECU
Asset C	1 ECU	5 ECUs	0 ECU



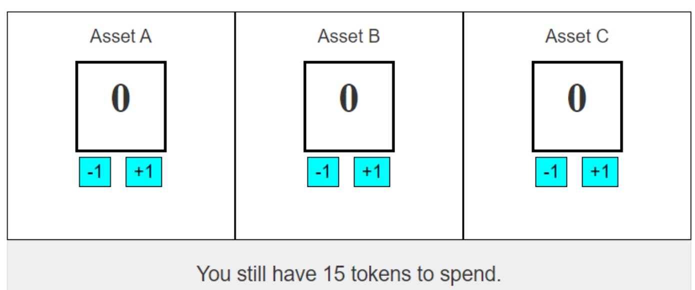


Figure IX. Allocation Decisions for Two Assets (Left) and Three Assets (Right)

Expected utility theory predicts that *any* risk-averse agent will allocate 9 tokens to Asset 1 and 3 tokens to Asset 2 in the two-asset condition as both assets have the same expected

[14]To keep the experimental design simple, we do not distinguish assets from categories in the experiment, implicitly assigning different assets to different categories. This might be particularly natural, for instance, if the assets are categorized by their riskiness. In our experiment, the assets can be ranked in precisely that way according to second-order stochastic dominance, as the assets are mean-preserving spreads.

[15]These stakes are consistent with the amount commonly paid in experiments conducted via Amazon Mechanical Turk. Subjects also received an additional \$1 payment for participating.

payoff and that particular allocation will perfectly equalize payoffs across the two states. In addition, EU predicts that any risk-seeking agent will allocate all 12 tokens to Asset B. Only in the knife-edge case in which the decision maker is exactly risk-neutral does EU not make a clear prediction: A risk-neutral EU agent will be indifferent between all possible allocations. In contrast, under our running parametric specification in (5, 6) with $u(x) = x$ and $\theta = 1$, a categorical thinker uniquely chooses the equal split allocation (six tokens to each asset) out of the 13 possible allocation strategies.

For the three-asset condition, EU predicts that *any* risk-averse agent will allocate 10 tokens to Asset A, 3 tokens to Asset B, and 2 tokens to Asset C, as each asset has the same expected payoff and that particular allocation will perfectly equalize payoffs across states. In addition, EU predicts that any risk-seeking agent will allocate 15 tokens to Asset C. A risk-neutral EU agent will be indifferent between all possible allocations. In contrast, under our running parametric specification in (5, 6) with $u(x) = x$ and $\theta = 1$, a categorical thinker uniquely chooses the equal split allocation (five tokens to each asset) out of the 136 possible allocation strategies.

The CST prediction of an equal allocation across assets is distinct from the predictions of the original salience theory of Bordalo et al. (2012). Under the original salience theory, an agent constructs the minimal state space from the support of the overall distribution of lottery payoffs. To simplify the problem, it is sufficient to show that under the original salience theory, the optimal CST allocation is dominated by the EU allocation. Under the optimal CST allocation (consistent with the 1/N rule), the portfolio pays 12 ECU's or 24 ECU's with equal probability, whereas the optimal EU allocation pays 18 ECU's with certainty. The minimal state space under original salience theory is then (12,18) and (24,18) and the original salience theory predicts that the EU allocation is chosen over the CST allocation for an agent with any salience function satisfying diminishing sensitivity and any linear or concave utility function. Similarly, for the three-asset allocation decision, the optimal CST portfolio pays 15 ECU's, 30 ECU's, or 45 ECU's with equal probability, whereas the optimal EU allocation pays 30 ECU's with certainty. The minimal state space under original salience theory is then (15,30), (45,30), and (30,30) and the original salience theory predicts that the EU allocation is chosen over the CST allocation for an agent with any salience function satisfying diminishing sensitivity and any linear or concave utility function.

The CST prediction is also distinct from that of cumulative prospect theory (CPT) due to Tversky and Kahneman (1992). Using the value function and probability weighting function from Tversky and Kahneman (1992) and the parameter estimates from the classic experimental studies of CPT cited in Neilson and Stowe (2002, p. 36) (Tversky and Kahneman (1992), Camerer and Ho (1994), or Wu and Gonzalez (1996)), we find that a CPT agent prefers the optimal EU allocation over the optimal CST allocation for both the two-asset and three-asset allocation decisions.

The CST further predicts there to be a framing effect in portfolio choice decisions. In the format presented in many retirement savings plans in which participants are asked to allocate their wealth across different asset categories, a CST agent will systematically deviate from true diversification (equalizing wealth across states) in the direction of naive diversification (equalizing wealth across categories). However, CST also provides a remedy to this sub-optimal investment bias: If participants are presented with the distribution of their portfolio returns across states, as shown for instance in Figure X, a CST agent with linear (or concave) utility will prefer Allocation 1 (corresponding to the optimal EU allocation) in both portfolio decisions for any salience function. In our experiment, the subjects who faced the two-asset (three-asset) allocation decision in Figure IX were subsequently asked to make a binary choice between two lotteries shown in Figure X, one option corresponding to the distribution implied by the 1/N allocation for two (three) assets (Allocation 2) and the other option corresponding to true diversification (Allocation 1). Since only the portfolio distribution ultimately matters, a CST agent with concave utility (i.e., who has preferences for diversification across states) but who allocates payoffs equally across categories would benefit from a policy which displayed the distribution of portfolio returns, thereby mitigating the bias due to categorization.[16]

State Salience

Portfolio (2-State Example)

	s_1	s_3
p	1/2	1/2
Allocation 1	18	18
Allocation 2	12	24

Portfolio (3-State Example)

	s_1	s_2	s_3
p	1/3	1/3	1/3
Allocation 1	30	30	30
Allocation 2	15	30	45

Figure X. Asset Allocation with Salient States

[16] After making their portfolio allocation decisions, subjects completed a risk-preference elicitation task based on Eckel and Grossman (2002) and the cognitive reflection test (Frederick, 2005).

4.2.2 Results

A total of 192 subjects completed the study, of whom 88 were randomly assigned to the two-asset condition and 104 were randomly assigned to the three-asset condition.[17] In both conditions, there was a wide dispersion of asset allocation choices. In the two-asset allocation condition, there are thirteen possible allocations (allocating any integer between 0 and 12 tokens to the safe asset). Figure XI shows the frequency of allocation decisions for the two-asset condition. Despite the variety of chosen allocations, the modal response was correctly predicted by CST (chosen by 19 of 88 subjects), whereas only 5 subjects chose the allocation predicted by EU for any risk-averse agent (EU-RA) allocating 9 tokens to the safe asset. Only two subjects chose the EU risk-seeking strategy (EU-RS) of purchasing only the risky asset. We also note that 13 subjects chose what one could term a 'naive' risk-averse strategy by allocating all 12 tokens to the safe asset. One could more generally categorize subjects as approximately CST or approximately EU-RA if their chosen allocation was one token away from the CST and EU-RA predictions, respectively. Under this categorization, 35 subjects are approximately CST while 30 are approximately EU-RA in their allocation decisions.

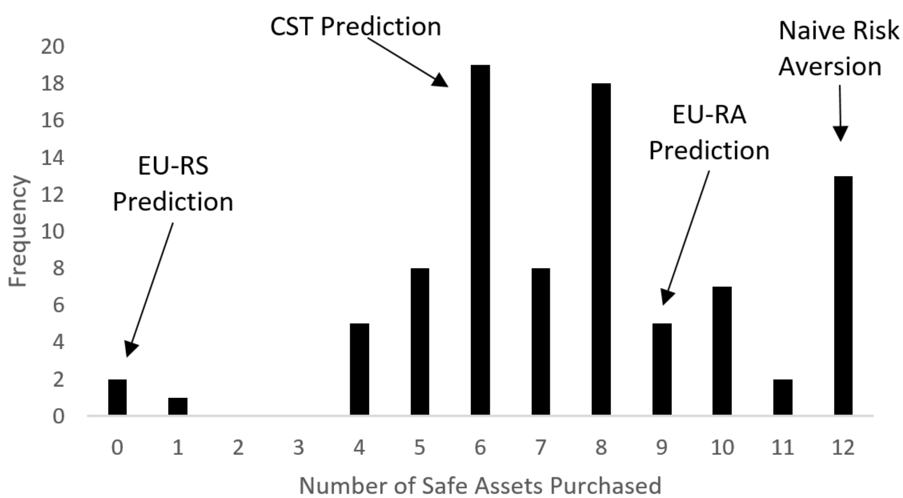


Figure XI. Frequency of Choices in Two-Asset Allocation Condition

The results for the three-asset allocation condition are even more supportive of CST. In that condition, there are 136 different possible allocation decisions. Despite the wide

[17] The sample size was set at 200, but the data was not recorded for one subject who started but did not complete the study. Seven other subjects were dropped from the data for violating the instructions by trying to complete the experiment twice or by entering a different subject ID from the one they were assigned. The number of subjects differed between the two conditions due to the random assignment. The objective of this study is descriptive, therefore the sample size was not based on power calculations, unlike the risky choice across categories experiment where a treatment effect was being measured.

dispersion of chosen allocations, as show in Figure XII, the modal response was predicted by CST (chosen by 17 of 104 subjects). No subject chose the EU-RA allocation strategy. There were 11 subjects who chose the 'naive' risk-averse strategy by only purchasing the safe asset. No subject followed the EU-RS strategy and no other allocation strategy was chosen by more than five subjects.

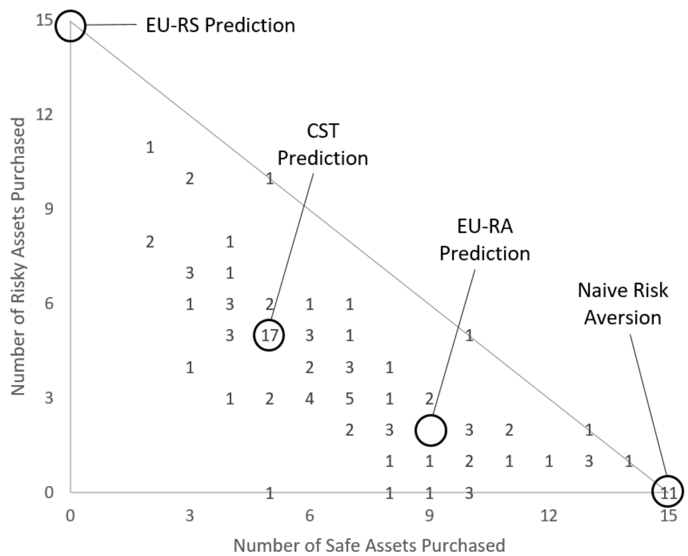


Figure XII. Frequency of Choices in Three-Asset Allocation Condition

Of the 88 subjects in the two-asset allocation condition, 51 chose Allocation 1 on the left side of Figure X. Behavior in the three-asset condition is even more stark. There, 79 of the 104 subjects chose Allocation 1 on the right side of Figure X. In both conditions, the majority choice is predicted by the CST and EU-RA models.

5 Categorization and Insurance

Insurance contracts and warranties are often highly specialized. For instance, it is common to see insurance companies offer flood insurance, fire insurance, and earthquake insurance, rather than offering a single comprehensive insurance policy against natural disasters. There is also evidence that consumers are willing to pay more for two specialized insurance policies covering mutually exclusive risks than they will pay for a single policy covering both of those risks. In a classic study, Johnson et al. (1993) found that the total amount respondents were willing to pay for two life insurance policies due to death from air travel - terrorism insurance and non-terrorism related mechanical failure, exceeded the amount they would pay for flight insurance that applied to any cause of death.

The CST predicts such effects to occur. Consider the choice problem given in Figure VI. In the left hand side of the figure, a consumer chooses whether to purchase two actuarially fair insurance policies to insure a potential \$1000 loss. One policy is for flood insurance, where the flood occurs with probability p. The other policy is for earthquake insurance where the earthquake occurs with probability q. For simplicity, we assume as in Gennaioli and Shleifer (2010) that at most one disaster occurs. In the right hand side of Figure VI, a consumer chooses whether to purchase a single insurance policy that applies to all natural disasters. Clearly this policy applies more broadly than to just flooding and earthquakes but in our illustration we let these be the only two risks so that the two choices in Figure VI have the same expected cost.

	Flood Insurance		Earthquake Insurance	
State	p	$1-p$	q	$1-q$
A	$-1000p$	$-1000p$	$-1000q$	$-1000q$
B	-1000	0	-1000	0

	Natural Disaster Insurance	
State	$p+q$	$1-p-q$
A	$-1000(p+q)$	$-1000(p+q)$
B	-1000	0

Figure VI. Categorized versus Comprehensive Insurance

For the choices in Figure VI, CST predicts that a consumer will be more inclined to purchase the flood and earthquake insurance policies than the natural disaster insurance since the smaller costs of the separately categorized insurance policies are less salient than the larger cost of the single-category policy. To illustrate, let $p = 0.01$ and $q = 0.02$ in Figure VI and let $u(x) = x$. Then a CST consumer would choose A over B in the choice on the left (insuring against the loss by purchasing flood insurance and earthquake insurance) if the following inequality holds:

$$[\sigma(-10, -1000) - \sigma(-10, 0)](9.9) > [\sigma(-20, 0) - \sigma(-20, -1000)](19.6).$$

In contrast, a CST consumer would choose B over A in the choice on the right (choosing not to purchase natural disaster insurance) if the following inequality holds:

$$\sigma(-30, -1000) < \sigma(-30, 0).$$

Under our running parametric specification (salience function (6) with $\theta = 1$), both of the above inequalities hold.

6 Categorization and Contracts

We next consider an application of CST to contract theory. In practice, employment contracts often feature non-monetary incentives such as bonus paid vacation time for good performance. A field experiment by Lockwood et al. (2010) found that a contingent time off (CTO) plan that rewarded high productivity with paid time off led to an increase in productivity at a manufacturing plant that persisted when productivity was measured six months after the intervention was implemented. From the perspective of neoclassical economics, monetary incentives should dominate non-monetary incentives of equivalent value because money has option value (Jeffrey, 2003) and employers are unlikely to know an employee's preference-maximizing choice for how to use that money.

From the perspective of CST, non-monetary incentives provide another category of outcomes in addition to wages, which due to diminishing sensitivity of salience perception, could incentivize agents to work even more than a marginally higher wage. To illustrate, consider a principal-agent problem with a risk-neutral principal and a CST agent where the agent chooses between two effort levels, $e \in \{0, 1\}$, and the principal wants to induce the agent to work ($e = 1$) rather than shirk ($e = 0$). There are two possible output levels for the principal, H and L, denoting high and low output, respectively. States are denoted $\{s_0, s_1\}$, indicating the output level for effort levels 0 and 1, respectively, where $s_0, s_1 \in \{L, H\}$. The probability of each state, p_{es}, depends on the agent's effort level where $p_{1H} > p_{0H}$.

To induce the agent to work, the principal chooses between two contracts. Contract A uses only monetary incentives. It pays the agent $\underline{w}$ if output is low and it pays $\overline{w} > \underline{w}$ if output is high. Contract B pays the agent a base salary, $\underline{w}$, in every state, and it gives the employee bonus paid time off (or some other non-monetary incentive) that has a monetary value equivalent to $\overline{w} - \underline{w}$ if the output is high. The agent has a cost of effort $c(e)$ normalized such that $c(0) = 0$ and $c(1) = c$. The two contracts are summarized from the agent's perspective in Figure VII.

A CST agent with linear utility chooses to work ($e = 1$) under Contract A if

$$\sigma(\overline{w}, \underline{w})(\overline{w} - \underline{w})[(p_{0L})(p_{1H}) - (p_{0H})(p_{1L})] - \sigma(-c, 0)(c) > 0. \tag{7}$$

A CST agent with linear utility chooses to work ($e = 1$) under Contract B if

$$\sigma(\overline{w} - \underline{w}, 0)(\overline{w} - \underline{w})[(p_{0L})(p_{1H}) - (p_{0H})(p_{1L})] - \sigma(-c, 0)(c) > 0. \tag{8}$$

Contract A (Monetary Incentives)

	Wage				Cost
State	$\{L,L\}$	$\{L,H\}$	$\{H,L\}$	$\{H,H\}$	1
$e=1$	$\underline{w}$	$\overline{w}$	$\underline{w}$	$\overline{w}$	$-c$
$e=0$	$\underline{w}$	$\underline{w}$	$\overline{w}$	$\overline{w}$	0

Contract B (Monetary and Non-Monetary Incentives)

	Base Salary				Cost	Bonus Paid Time Off			
State	$\{L,L\}$	$\{L,H\}$	$\{H,L\}$	$\{H,H\}$	1	$\{L,L\}$	$\{L,H\}$	$\{H,L\}$	$\{H,H\}$
$e=1$	$\underline{w}$	$\underline{w}$	$\underline{w}$	$\underline{w}$	$-c$	0	$\overline{w}-\underline{w}$	0	$\overline{w}-\underline{w}$
$e=0$	$\underline{w}$	$\underline{w}$	$\underline{w}$	$\underline{w}$	0	0	0	$\overline{w}-\underline{w}$	$\overline{w}-\underline{w}$

Figure VII. Contracts with Monetary and Non-Monetary Incentives

By diminishing absolute sensitivity,

$$\sigma(\overline{w},\underline{w}) = \sigma(\overline{w}-\underline{w}+\underline{w}, 0+\underline{w}) = \sigma(\overline{w}-\underline{w}+\epsilon, \epsilon) < \sigma(\overline{w}-\underline{w}, 0).$$

Thus, for any salience function, the CST agent is more sensitive to the non-monetary incentive than to a marginally higher wage. If the agent were indifferent between working and shirking under contract A, the agent would strictly prefer to work under contract B. If the agent prefers to work under both contracts, the above analysis implies that the principal could lower the non-monetary incentive under Contract B and thereby have a lower expected payment than under Contract A but still induce the agent to work. This prediction also has empirical support. Choi and Presslee (2016) conduct an experiment using a real-effort task to investigate the performance effects of tangible (non-monetary) incentives versus cash rewards and they find a mediating role of categorization. They report: “performance increases the more participants categorize performance-contingent pay separately from salary.”

7 Conclusion

We provided a generalization of salience theory called categorical salience theory (CST) to risky choices over multidimensional outcomes. In this richer setting, we derive two novel predictions of CST in the context of choices between lotteries: (i) Risk aversion will be greater for money (or a single consumer good) than for different types of consumer goods (or a combination of money and goods), and that (ii) one of the most robust empirical violations of EU, the Allais common ratio effect, will disappear when the outcomes consist of different types of goods (or a combination of money and goods). These are strong predictions of CST because (i) the predictions are systematic (the reverse predictions do not hold) and (ii) the predictions are novel (they are not shared by alternative models). These predictions are also supported by recent experimental results that on their own seem surprising (e.g., Arroyos-Calvera et al., 2018; DeJarnette, 2017), and by our lab-in-the-field experiment on risky choices across categories designed to test CST.

We demonstrated that CST offers explanations for empirical puzzles across a variety of contexts including the higher willingness to pay for categorized insurance, the effectiveness of non-monetary incentives in labor contracts, and greater variety seeking in simultaneous than in sequential choice. Moreover, the same simple parametric specification is sufficient to explain each puzzle studied in this paper. We also found that CST predicts majority behavior consistent with naive diversification in portfolio choice in a new online experiment. In each application, the predictions of CST are systematic and they are distinct from other models of choice under risk.

The predictive success of CST is not derived from added flexibility. For a given categorization of outcomes, CST generalizes the Bordalo et al. (2012) salience model *without* adding parameters. Further, CST has *fewer* parameters than cumulative prospect theory. The original version of salience theory can explain the classical empirical phenomena that prospect theory can also accommodate[18], while CST delves into uncharted territory by linking the basic concepts of salience perception and categorization to choices under risk.

[18] Bordalo et al. (2012) do demonstrate that salience theory can explain differences in behavior toward correlated and independent lottery payoffs and preference reversals between choice and pricing tasks that also distinguish salience theory from cumulative prospect theory for monetary lotteries.

Appendix

In this appendix we show that the measure of contrast between two payoffs in a choice set given by equation (6) coincides with a measure of visual contrast between two pixels in an image used in computational neuroscience. Raj et al. (2005), Frazor and Geisler (2006), and Chen and Blum (2009) use the following formula to measure visual contrast between pixels in an image (where L_i is the luminous intensity of pixel i):

$$C = \sqrt{\frac{1}{\sum_{i=1}^{N} w_i} \sum_{i=1}^{N} w_i \frac{(L_i - L)^2}{(L + L_0)^2}}. \tag{9}$$

In (9), $L_0 \geq 0$ is a constant and $L > 0$ is a weighted average of the luminous intensities:

$$L = \frac{1}{\sum_{i=1}^{N} w_i} \sum_{i=1}^{N} w_i L_i. \tag{10}$$

Proposition A.1 (Equivalence between visual contrast and payoff contrast): *For $N = 2$ pixels, with luminous intensities $L_1, L_2 \geq 0$, and mean $L = \frac{1}{2}(L_1 + L_2) > 0$, the formula for visual contrast in (9) is equivalent to the formula for payoff salience in (6).*

Proof: Given $N = 2$, $L_1, L_2 \geq 0$, and $L = 0.5L_1 + 0.5L_2$, formula (9) reduces to:

$$C = \sqrt{0.5\left(\frac{L_1 - 0.5L_1 - 0.5L_2}{0.5L_1 + 0.5L_2 + L_0}\right)^2 + 0.5\left(\frac{L_2 - 0.5L_1 - 0.5L_2}{0.5L_1 + 0.5L_2 + L_0}\right)^2}$$

The above formula simplifies to:

$$C = \sqrt{\left(\frac{L_1 - L_2}{L_1 + L_2 + 2L_0)}\right)^2} = \frac{|L_1 - L_2|}{L_1 + L_2 + \theta}$$

where $\theta \equiv 2L_0$. □

References

1. Allais, M. 1953. Le comportement de l'homme rationnel devant le risque: critiques des postulats et axioms de l'ecole Americaine. *Econometrica* 21, 503-546.

2. Arroyos-Calvera, D., A. Isoni, G. Loomes, R. McDonald. 2018. "The common ratio effect with objects and money." Foundations of Utility and Risk, Book of Abstracts. https://www.furconference.org/wp-content/uploads/2018/07/Book-of-Abstracts-2.pdf

3. Barberis, N., M. Huang. 2008. Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066-2100.

4. Bell, D. 1982. Regret in decision making under uncertainty. *Operations Research* 20, 961-981.

5. Bell, D. 1985. Disappointment in decision making under uncertainty. *Operations Research* 33, 1- 27.

6. Benartzi, S., R.H. Thaler. 2001. Naive diversification strategies in defined contribution saving plans. *American Economic Review* 91, 79-98.

7. Bordalo, P., Gennaioli, N., Shleifer, A. 2012. Salience theory of choice under risk. *Quarterly Journal of Economics* 127, 1243-1285.

8. Bordalo, P., Gennaioli, N., Shleifer, A. 2013a. Salience and consumer choice. *Journal of Political Economy* 121, 803-843.

9. Bordalo, P., Gennaioli, N., Shleifer, A. 2013b. Salience and asset prices. *American Economic Review* 103, 623-28.

10. Camerer, C.F., T. Ho. 1994. Violations of the betweenness axiom and nonlinearity in probability. *Journal of Risk and Uncertainty* 8, 167-196.

11. Chen, Y., R.S. Blum. 2009. A new automated quality assessment algorithm for image fusion. *Image and Vision Computing* 27, 1421-1432.

12. Choi, W., A. Presslee. 2016. "The performance effects of tangible versus cash rewards: The mediating role of categorization." Manuscript.

13. DeJarnette, P. 2017. Risky Choices over Goods. Unpublished manuscript. https://site.stanford.edu/sites/default/files/riskychoicesovergoods.pdf

14. Eckel, C.C., P.J. Grossman. 2002. Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior* 23, 281-295.

15. Frazor, R.A., W.S. Geisler. 2006. Local luminance and contrast in natural images. *Vision Research* 46, 1585-1598.

16. Frederick, S. 2005. Cognitive reflection and decision making. *Journal of Economic Perspectives* 19, 25-42.

17. Frydman, C., M.M. Mormann. 2018. The role of salience in choice under risk: An experimental investigation. papers.ssrn.com/sol3/Papers.cfm?abstract_id=2778822

18. Gennaioli, N., Shleifer, A. 2010. What comes to mind. *Quarterly Journal of Economics* 125, 1399-1433.

19. Golec, J., M. Tamarkin. 1998. Bettors love skewness, not risk, at the horse track. *Journal of Political Economy* 106, 205-225.

20. Harnad, S. 2017. To cognize is to categorize: Cognition is categorization. In: *Handbook of Categorization in Cognitive Science*, (Second Edition), Cohen, H., and Lefebvre, C. (Eds), Elsevier. Chapter 2, 21-54.

21. Herweg, F., D. Müller. 2019. Regret theory and salience theory: Total strangers, distant relatives, or close cousins? CESifo working paper no. 7445.

22. Jeffrey, S. 2003. Non-monetary incentives and motivation: When is Hawaii better than cash? Manuscript.

23. Johnson, E.J., J. Hershey, J. Meszaros, H. Kunreuther. 1993. Framing, probability distortions, and insurance decisions. *Journal of Risk and Uncertainty* 7, 35-51.

24. Kahneman, D., A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47, 263-292.

25. Karni, E. 1979. On multivariate risk aversion. *Econometrica* 47, 1391-1401.

26. Koszegi, B., F. Matejka. 2019. Choice simplification: A theory of mental budgeting and naive diversification. https://economics.harvard.edu/files/economics/files/ms29833.pdf

27. Landry, P., R. Webb. 2020. Pairwise normalization: A neuroeconomic theory of milti-attribute choice. Manuscript.

28. Leland, J., Schneider, M., Wilcox, N. 2019. Minimal frames and transparent frames for risk, time, and uncertainty. *Management Science*, 4318-4335.

29. Lichtenstein, S., Slovic, P. 1971. Reversals of preference between bids and choices in gambling decisions. *Journal of Experimental Psychology* 89, 46-55.

30. Lockwood, D.L., Frayne, C., Stephenson, H. and Geringer, J.M. 2010. The impact of contingent time off on productivity in a small manufacturing environment, *Journal of Management and Marketing Research*, 3, 1-5.

31. Loomes, G., R. Sugden. 1982. Regret theory: An alternative theory of rational choice under uncertainty. *Economic Journal* 92, 805-824.

32. Loomes, G., R. Sugden. 1986. Disappointment and dynamic consistency in choice under uncertainty. *Review of Economic Studies* 53, 271-282.

33. McCoy, A., M. Platt. 2005. Risk-sensitive neurons in macaque posterior cingulate cortex. *Nature Neuroscience* 8, 1220-1227.

34. Nielsen, C.S., A.C. Sebald, P.N. S⌀rensen. 2018. Testing for salience effects in choices under risk. Manuscript.

35. Neilson, W., J. Stowe. 2002. A further examination of cumulative prospect theory parameterizations. *Journal of Risk and Uncertainty* 24, 31-46.

36. O'Donoghue, T., J. Somerville. 2018. Modeling risk aversion in economics. *Journal of Economic Perspectives* 32, 91-114.

37. Pandelaere, M., Briers, B., Lembregts, C. 2011. How to make a 29% increase look bigger: The unit effect in option comparisons. *Journal of Consumer Research* 38, 308-322.

38. Prelec, D., Loewenstein, G. 1991. Decision making over time and under uncertainty: A common approach. *Management Science* 37, 770-786.

39. Raj, R., W.S. Geisler, R.A. Frazor, A.C. Bovik. 2005. Contrast statistics for foveated visual systems: fixation selection by minimizing contrast entropy. *Journal of the Optical Society of America* 22, 2039-2049.

40. Read, D., G. Loewenstein. 1995. Diversification bias: Explaining the discrepancy in variety seeking between combined and separated choices. *Journal of Experimental Psychology: Applied* 1, 34-49.

41. Rochanahastin, N., Schneider, M., Leland, J. 2018. Salience perception and skewness preference: A test of salience theory for choice under risk. Manuscript.

42. Simonson, I. 1990. The effect of purchase quantity and timing on variety-seeking behavior. *Journal of Marketing Research* 27, 150-162.

43. Starmer, C., R. Sugden. 1993. Testing for juxtaposition and event-splitting effects. *Journal of Risk and Uncertainty*, 6, 235-254.

44. Tversky, A., Kahneman, D. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5, 297-323.

45. Wertenbroch, K., Soman, D., Chattopadhyay, A. 2007. On the perceived value of money: The reference dependence of currency numerosity effects. *Journal of Consumer Research* 34, 1 – 10.

46. Wu, G., R. Gonzalez. 1996. Curvature of the probability weighting function. *Management Science* 42, 1676-1690.